

MULTI-TASK GLOH FEATURE SELECTION FOR HUMAN AGE ESTIMATION

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ABSTRACT

In this paper, we propose a novel age estimation method based on gradient location and orientation histogram (GLOH) descriptor and multi-task learning (MTL). The GLOH, one of the state-of-the-art local descriptor, is used to capture the age-related local and spatial information of face image. As the extracted GLOH features are often redundant, MTL is designed to select the most informative GLOH bins for age estimation problem, while the corresponding weights are determined by ridge regression. This approach largely reduces the dimensions of feature, which can not only improve performance but also decrease the computational burden. Experiments on the public available FG-NET database show that the proposed method can achieve comparable performance over previous approaches while using much fewer features.

Index Terms— Age estimation, GLOH feature, multi-task learning, ridge regression

1. INTRODUCTION

Within the past decade, automatic age estimation has become an active research topic due to its emerging new applications from human-computer interaction to security control, surveillance monitoring, biometrics, etc. For example, in automatic human computer interaction (HCI) applications if computers can determine the age of the user, both the content of computer and the type of interaction can be adjusted according to the age of the user. In security control and surveillance monitoring, the automatic age estimation system can prevent minors from drinking wine or purchasing tobacco.

Aging is a very complicated process and is determined by both innate factors and environmental factors such as heredity, gender, health, and lifestyle, which make the automatic age estimation very challenging. Much works on age estimation problem has been undertaken in recent years. Two keys to these methods are face representation and age estimation [1]. Existing face representation techniques for age estimation often include the anthropometric models [2], active appearance models [3, 4, 5], aging pattern subspace [6], age manifold [7, 1, 8], local features such as local binary patterns (LBP) features [9], Gabor features [10], spatially flexible

patch (SFP) [11], bio-inspired features (BIF) [12], etc. and the combination of them [13, 14]. Based on these face representation, the age estimation can be performed by considering it as a classification problem [2, 3, 4, 6, 9, 14] or a regression problem [11, 12, 13, 3, 4, 5] or a hybrid of two [1]. It is well known that aging process shares a global trend but is specific to a given individual. Most of existing methods concern the building of global age estimator [10, 12, 11] due to the lack of training data for each individual. There are also a few works care on the person specific age estimation [3, 4, 6, 5].

In this paper we propose a novel method based GLOH representation [15] and MTL feature selection [16] along with ridge regression for global age estimation. The basic idea is to use the state-of-the-art GLOH descriptor to represent the age-related local and spatial information in the face image and utilize a sparsity-enforced MTL to select the most informative GLOH bins. The selected GLOH bins can be seen as a discriminant and compact face representation and are fed into ridge regressors to estimate the age. Fig. 1 illustrates the framework of our method.

To the best of our knowledge, the GLOH descriptor and regularization based feature selection method are applied to age estimation research for the first time. We propose to use individual bins, instead of the whole histogram, of GLOH as feature for selection and estimation. We use the ridge regression on the selected feature for estimation instead of using the original sparsity-enforced linear regression, which can avoid the underestimation problem of the coefficients induced by the sparsity-enforced linear regression.

The rest of the paper is organized into several sections. In section 2, we describe the GLOH-based face representation. Section 3 details the sparsity-enforced multi-task feature (bin) selection and the ridge regression-based estimation. In section 4 we show the experimental results and analysis. Finally the section 5 concludes the paper.

2. GLOH REPRESENTATION

The GLOH local descriptor, originally introduced by Mikolajczyk et al. [15], is designed to increase the robustness and distinctiveness of the well-known SIFT descriptor which integrates both local appearance and position information. Simi-

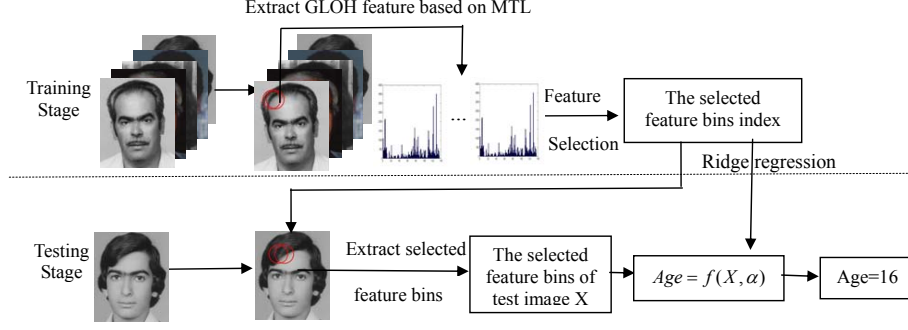


Fig. 1. The framework of the proposed method

lar to SIFT descriptor or HOG descriptor, it is also based on evaluating well-normalized local histograms of image gradient orientations in a dense grid. More specifically, the original GLOH descriptor can be obtained by computing the SIFT or HOG descriptor for a log-polar location grid with three radius and eight angles. The gradient orientations are then quantized into 16 parts and thus the resulting descriptor gives a 272-bins histogram. The size are reduced into 128 by PCA.

In our implementation, the parameters of GLOH descriptors are tuned to make it more suitable for our age estimation application. More details will illustrate in section 4. In order to obtain the GLOH representation of the face image, we first divide each face image into patches with overlaps, and then compute the GLOH histogram for all patches independently. Finally, we concatenate all these GLOH histograms to a high dimensional GLOH histogram vector, which is the representation for the image containing both the local texture feature and spatial information. Note that we don't perform PCA to reduce the GLOH dimensionality.

As we extract the GLOH feature from patches with overlaps, they are redundant. However, only a relatively small fraction of them is relevant to the estimation task. So feature selection is a crucial and necessary step to select the most discriminant ones, which can not only improve the estimation performance but also decrease the computational burden. In the next section we will describe how to adopt the sparse-enforced regularized-based method for feature (bins) selection.

3. MULTI-TASK GLOH FEATURE SELECTION

Assuming there is L tasks and the training set consists of samples $\{(\mathbf{x}_i^l, y_i^l) \in \mathcal{X} \times \mathcal{Y}, i = 1 \dots N_l, l = 1 \dots L\}$ where l indexes the tasks and i indexes the samples of each task, $\mathbf{x} \in \mathfrak{R}^K$ and $y \in \mathfrak{R}^1$ are the GLOH feature and age label, respectively, and N_l is the sample size of task l . If we treat the training of each task independently, the feature selection can be formulated as a sparsity regularized regression on their

age labels in terms of the GLOH bins

$$\min_{\mathbf{w}^l} \frac{1}{N_l} \sum_{i=1}^{N_l} J^l(\mathbf{w}^l, \mathbf{x}_i^l, y_i^l) + \lambda \|\mathbf{w}^l\|_1. \quad (1)$$

Due to the small sample size of each task, such a independent feature selection often leads to overfitting, which can be combated by the following multi-task generalization [16]

$$\min_{\mathbf{W}} \frac{1}{N_l} \sum_{i=1}^{N_l} J^l(\mathbf{w}^l, \mathbf{x}_i^l, y_i^l) + \lambda \sum_{k=1}^K \|\mathbf{w}_k\|_2, \quad (2)$$

where $\mathbf{W} = (\mathbf{w}_i^l)$ is the matrix with $\mathbf{w}^l \in \mathfrak{R}^K$ in rows and \mathbf{w}_k in columns.

In our implementation, we treat the age estimation of each gender as a task, since there is a significant difference in the timing and types of facial growth between men and women. In addition, we restrict ourselves to the case of a age regression model where the age is linear in the GLOH bins and then the loss function is given by

$$J^l(\mathbf{w}^l, \mathbf{x}_i^l, y_i^l) = \|y_i^l - \langle \mathbf{x}_i^l, \mathbf{w}^l \rangle\|_2^2. \quad (3)$$

We argue that linear methods are more preferred than non-linear ones due to the much faster training and testing speed and significantly less memory requirements, especially in the cases involving tens of thousands of samples with dimensionality of tens of thousands.

Notice that the optimization problem (2) is a non-smooth problem and in [16], the block-coordinate descent method is proposed to solve it directly. However, the block-coordinate descent is an iterative procedure which may converge slowly. In our implementation, we adopt the accelerated algorithm in [17] which reformulates it as two equivalent smooth convex optimization problems which are then solved via an optimal first-order black-box method for smooth convex optimization.

Recalled that the above feature selection frame yields both the selected feature bin indices and the corresponding coefficients and thus can be used for estimation directly. However,

one can also consider its usage as a pure feature selection tool and adopt some other common classifiers or regression methods for estimation. Experientially, the above feature selection frame often underestimates the coefficients and thus often can not achieve satisfied performance. We adopt the ridge regression method on the selected feature bins to alleviate this problem.

4. EXPERIMENTAL RESULTS

We carry experiments on the FG-NET aging database [18] to verify the proposed age estimation method. The database includes 1,002 images (82 persons) age ranging from 0 to 69. First, we align all images into the mean shape, the aligned face images are scale to the size of 68×62 . During the GLOH feature extraction step, the size of image patch is set as 10×10 . For each image patch, we use 3 radius $\{2, 3, 5\}$ and the 8 gradient directions used in each image patch, so the dimension of the resulting histogram vector is 136. By concatenating all patches histogram vector, we obtain a 48,960-dimensional original GLOH feature vector. It contains both the local texture and space information of the face image. The sparsity-enforced feature selection are applied to these high-dimensional GLOH features and no more than 50 bins are often selected in our experiments for the age estimation.

First we following the leave one person out (LOPO) rules in [6, 12]. For each fold, all the images of one person are set aside as the test set and those of the others are used as the training set to simulate the situation in real applications. The mean absolute error (MAE) is adopted as the performance measures. We also implement the single task learning (STL)-based methods. The result as showed in Table 1. Note that our method perform better than other methods except BIF-based method [12] and the MTL-based method is superior than the STL-based method. In order to perform a fair comparison with the BIF-based, we re-implement the method in [12], where BIF is extracted by the code ¹ and the regression through the code of LIBSVM ². Other parameters are set same as [12]. Although the MAE of their method shows in the paper reach 4.77, we just get 7.79. This difference may due to the different pre-process steps. Since the BIF is the state-of-the-art features for age estimation, we further compare the efficiency of BIF and GLOH feature in the same framework with different regressors and using PCA (keeping 98% energy) to reduce the dimensionality. Table 2 lists the comparative results, which shows that GLOH performs comparable or even better than BIF in age estimation. Moreover, the MTL-based dimensionality reduction performs much better than PCA.

Second, following the protocol in [8], we select 854 images with ages from 0 to 30 years (499 males and 355 females) as done in [8]. The performance is reported by cross-

Table 1. Prediction errors (in MAE) of different algorithms

Methods	MAE
AAS [6]	14.83
WAS [6]	8.06
AGES [6]	6.77
RUN1 [6]	5.78
BIF [12]	4.77(7.79)
GLOH+STL+Ridge regressor	5.83
GLOH+MTL+Ridge regressor	5.45

Table 2. Comparative performance of BIF and GLOH for age estimation with different dimensionality reduction tools and regressors

Method	MAE
BIF+PCA+Ridge regressor	8.81
BIF+PCA+SVR	7.79
GLOH+PCA+Ridge regressor	8.86
GLOH+PCA+SVR	7.36
GLOH+MTL+Ridge regressor (our method)	5.45

validation method. The whole process is repeated by leave-one-out mode as the same in [8]. We compare the result of our method with the reported methods in [8]. Table 3 summarizes the results based on the MAE. Our method performs better than others again. In addition to the MAE measures, we also explore the cumulative score as the performance measure. Figure 3 illustrates the comparative performance in terms of the cumulative accuracy which shows that our method performs better than the other two methods consistently and achieves a 96% accuracy rate on the 10-year tolerant error.

5. CONCLUSIONS

In this paper, we have proposed a novel age estimation framework based on GLOH feature and MTL. By using GLOH feature to represent face image and using multi-task learning to select features, we can select a few informative feature bins for age estimation. Ridge regression was adopted to confirm the weights of the selected feature bins. With them, we obtain an age regression model, the method takes advantages of low-dimension, high discriminative power and favorable performance over previous approaches.

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¹<http://cbcl.mit.edu/software-datasets/standardmodel/index.html>

²<http://www.csie.ntu.edu.tw/~cjlin/libsvm/>

Table 3. The comparative performance in terms of MAE using the protocol in [8]

Method	MAE	Std
APM+NN [8]	5.43	4.33
OLPP+NN [8]	4.93	3.89
Combined features+NN [8]	4.28	3.63
APM+QF [8]	4.29	3.55
OLPP+QF [8]	4.05	3.42
Combined features+QF [8]	3.65	3.06
Our method	3.44	2.88

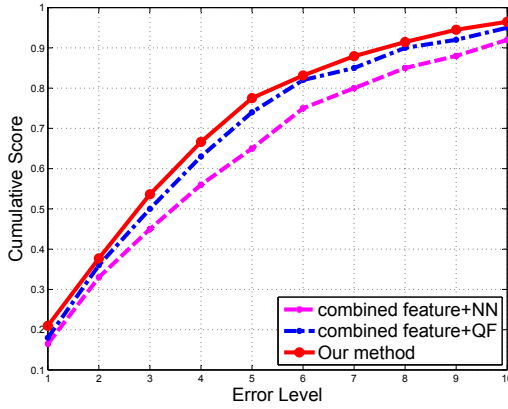


Fig. 2. The comparative performance in terms of Cumulative Scores using the protocol in [8]

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